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Research Article

Soft Computing Techniques for Minimizing and Predicting Average Localization Error in Wireless Sensor Networks

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Abstract:

Localization methods are used to approximate the position of unknown nodes in a network. Localization errors are calculated by comparing the estimated and true positions at each time step. Finding the best network parameters to minimize localization error during the network setup process while maintaining the requisite accuracy in a short period remains a difficult task. Both unknown and anchor nodes are strategically placed to reduce localization problems, which addresses a time series issue. Soft computing approaches such as Fuzzy Logic and Adaptive Neuro-Fuzzy Inference System (ANFIS) are used to address this issue. In this study, the number of nodes and network simulation area are used as de facto parameters for Average Localization Error(ALE) training and prediction. These feature values were obtained from simulations using the modified centroid localization technique with Kalman filter. This work tries to reduce localization errors by adjusting these parameters using soft computing techniques. The experimentation is carried out in MATLAB, demonstrating the suggested method's ability to improve reliability and reduce localization errors in wireless sensor networks.

1. Introduction

Wireless Sensor Networks (WSNs)[1] have become a crucial technology for various applications, including environmental monitoring, precision agriculture, target tracking, and many others. Accurate location of these sensors is essential for the effective operation of WSNs, as it directly impacts data correlation, node addressing, query management, node density evaluation, coverage analysis, energy mapping, geographic routing, and object tracking.

In the majority of applications, these sensors must precisely estimate their coordinates while minimizing resource consumption. These sensors can quickly determine their coordinates utilizing an integrated Global Positioning System (GPS). Nonetheless, integrating GPS into all sensors is not practically feasible due to its size and expense. An alternative method involves employing localization algorithms, wherein many anchor nodes equipped with GPS facilitate the precise determination of coordinates for unknown nodes. A wide range of localization algorithms has been developed to address various localization challenges. These algorithms are anticipated to be adaptable, enabling effective performance across a range of various indoor and outdoor settings and topologies.

Traditional localization algorithms [2-10] in Wireless Sensor Networks (WSNs) fall into two categories: range-based and range-free. Traditional localization methods often suffer from uncertainties and imprecisions, especially in dynamic and complex environments. This necessitates the need for more adaptive and robust techniques to minimize localization errors and enhance reliability. Soft computing techniques [11-16], including fuzzy logic [12,13,14,15,17,18-26] and Adaptive Neuro-Fuzzy Inference Systems (ANFIS)[19,20-30], offer a promising solution to address these challenges. These techniques can handle the inherent uncertainties and imprecisions in sensor data, providing a more flexible and robust approach to localization.

The study investigated several fuzzy-related strategies that could help both academics and practitioners with WSN localization. Uncertainty and imprecision frequently provide challenges to WSN localization, which differs in technology, sensory information, communication protocols, algorithms, and accuracy. Fuzzy logic, which is based on fuzzy sets, represents human reasoning and successfully handles imprecision. These technologies provide an acceptable solution to the issues encountered in various localization procedures. Fuzzy sets and inference systems give flexibility and robustness without the requirement for precise mathematical models, making them appropriate for complicated behaviors.

Tanveer Ahmad et al.[13] proposed a fuzzy logic based localization for mobile sensors node . Mobile anchors gather data on RSSI versus distance during training. For each unknown sensor, a circle is drawn around a nearby anchor based on strongest signal, with its radius estimated from training data. Fuzzy logic then weighs anchor locations based on signal strength. Finally, the most accurate location is calculated as the midpoint where a line perpendicular to the circle intersects the weighted center from the fuzzy logic step.

Gilean C et al,[14] proposed a fuzzy logic technique to optimize data delivery time and energy efficiency in wireless sensor networks (WSNs). Implemented in MATLAB, the system considers node status and message type to decide data transmission. Simulations show larger packets increase delivery time and energy consumption. The fuzzy logic algorithm improves WSN performance, offering a promising approach to balance transmission efficiency and energy conservation.

Taner Tuncer et al.[15] proposed the Intelligent Centroid Localization (ICL) method is a novel approach for improving location accuracy in wireless sensor networks. It controls fuzzy logic and a genetic algorithm to analyse signal strength (RSSI) from anchor nodes, giving more weight to stronger signals for better positioning. Compared to traditional techniques, ICL significantly reduces location error.

Sadik Kamel Gharghan et al. [21] described two soft computing localization algorithms for wireless sensor networks (WSNs): the neural fuzzy inference system (ANFIS) and the artificial neural network (ANN). Both methods utilize the ZigBee anchor nodes' received signal strength indicator (RSSI) for range-based localization. The first technique employs ANFIS, whereas the second method enhances ANN with optimization algorithms including GSA, BSA, and PSO. The results reveal that the hybrid GSA-ANN method delivers the best distance estimate accuracy, making it the most effective solution for both indoor and outdoor contexts.

V. P. Kavitha et al. [22] proposed a new method for sensor node localization in Wireless Sensor Networks (WSNs) that employs the Adaptive Neuro Fuzzy Logic Inference System. The authors compare their method to Fuzzy Logic Control (FLC) and conclude that ANFIS performs better in terms of security, accuracy, and optimal sensor node placement. Simulations show that ANFIS is considerably more accurate than FLC.

Noura BACCAR et al.[23] proposed a novel adaptive fuzzy localization system for Wireless Sensor Networks (WSNs), utilizing a Fuzzy Location Indicator (FLI) to create fuzzy sets representing rooms as adjacent zones on a building map. The system employs a Sugeno type-0 fuzzy inference model and undergoes supervised learning via the ANFIS algorithm. Fingerprints, collected as received signal strengths (RSSI) from different anchors, are associated with each FLI.

ABHILASH SINGH et al. [24] introduced an efficient machine learning strategy that employs a Support Vector Regression (SVR) model to assess network parameters that minimize Average Localization Error (ALE). Three SVR-based methods—S-SVR, Z-SVR, and R-SVR—are proposed that use feature standardization techniques. These approaches use anchor ratio, transmission range, node density, and iterations as features, which are generated from modified Cuckoo Search (CS)[29] simulations.

Isaac Kofi Nti et al.[25] proposed an optimized random forest-based model with fine-tuned hyperparameters to predict Average Localization Error (ALE) in wireless sensor networks (WSNs). The study identified key parameters, including node density, anchor ratio, transmission range, and iterations, influencing node localization. The model achieved rapid, accurate ALE predictions, highlighting the critical factors impacting WSN setup efficiency.

The average localization error (ALE) metric measures the accuracy of localization methods. The performance of these methods may vary over time due to a variety of parameters, including network simulation area, node count, communication range, and node deployment models. In any network configuration, it is critical to run the algorithm several times to identify the ideal network parameters and fine-tune the ALE for a minimal localization error in the desired situation. However, traditional localization algorithms frequently meet uncertainty and imprecision, making them

unsuitable for dynamic real-world situations. Use soft computing techniques to solve this challenge. Integrating soft computing techniques enhances localization accuracy greatly when compared to traditional techniques.
This study developed a new method for predicting and minimizing localization errors in WSNs by tuning the de facto parameters with soft computing approaches. Integrating fuzzy logic and ANFIS improves the reliability of localization systems while significantly decreasing localization errors as compared to traditional approaches. First, use fuzzy logic to simulate the uncertainties and imprecisions in parameter fluctuations. Second, use ANFIS to identify complex correlations between parameters. Training on historical data allows ANFIS to adaptively adjust the localization model and improve its prediction capabilities. The suggested approach combines the best features of fuzzy logic and ANFIS to increase network reliability and reduce the localization errors in wireless sensor networks

2. Methodology

The initial implementation of a range-free centroid localization algorithm yielded unacceptable levels of localization inaccuracy. Adding a Kalman filter [27] to the method makes the estimated positions for unknown nodes more accurate and lowers the number of errors in localization. Experiments are conducted in MATLAB, varying the simulation areas, communication ranges, node numbers, and deployment modes. The performance of the algorithm is evaluated using the average localization error, defined as the difference between the true and estimated positions.
Taguchi technique [28] to identify the most influential factors for localization error. The investigation found that the number of nodes and the simulation area had the greatest impact on localization errors in wireless sensor networks (WSNs). Hence, choose these two parameters as the key tuning elements in the FUZZY model to predict and minimize localization errors. In this study, the number of nodes and the network simulation area are key parameters for tuning and training the average localization error (ALE) in wireless sensor networks Fuzzy sets are created to represent these input parameters, using membership functions to capture the underlying uncertainty.
A fuzzy rule base was established to link the inputs (number of nodes and simulation area) to the potential output (ALE), where fuzzification converts precise input data into fuzzy sets, and defuzzification translates fuzzy outputs back into exact values. ANFIS optimizes the membership functions and rules using a hybrid learning algorithm that

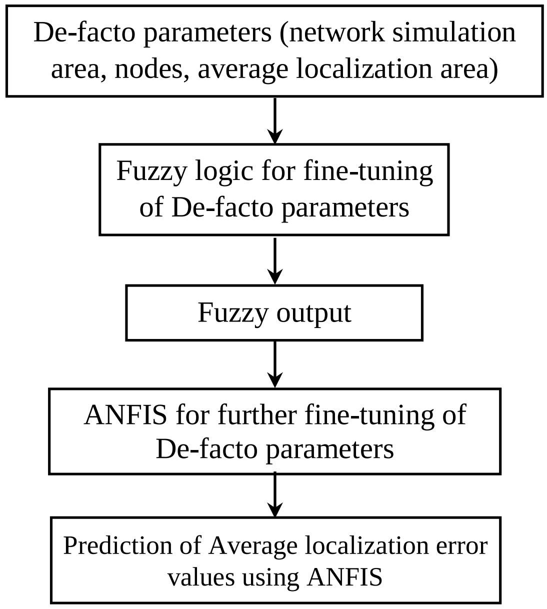

Figure 1. *Schematic of Research Methodology*

combines backpropagation with least-squares estimation.This approach effectively integrates Fuzzy Logic and the Adaptive Neuro-Fuzzy Inference System (ANFIS), enhancing localization accuracy by addressing challenges posed by measurement uncertainties and dynamic environments. The schematic diagram of research methodology, is illustrated in Figure 1

3. FUZZY Based System to tune the parameters to Predict and minimize the Average Localization Error

A FUZZY-based system is used to fine-tune parameters and reduce localization errors in wireless sensor networks. The system uses Fuzzy Logic to optimize localization accuracy by adjusting important parameters such as number of nodes and network simulation area. The FUZZY-based system includes the following steps:

➢ The system translates precise input data (number of nodes and simulation area) into fuzzy sets, indicating the degree of uncertainty or unpredictability. Membership functions define fuzzy sets by capturing the range of possible values.

➢ The Fuzzy Rule Base is a set of rules that connect fuzzy inputs to expected output (Average Localization Error). These rules define the link between the parameters and the localization error, allowing the system to determine how changes in input values affect the error.

➢ The system uses fuzzy rules to process inputs and provide outputs that estimate localization error. This phase uses Fuzzy Logic techniques to reason about uncertainty.

➢ Defuzzification: The fuzzy output is turned to a precise numerical number for the Localization Error, allowing the system to provide particular feedback on parameter settings.

➢ The optimization technique iteratively modifies parameters to minimize Localization Error. This fuzzy-based system increases localization accuracy in dynamic network contexts by dynamically modifying its parameters, reducing the impact of measurement errors.

3.1 Fuzzy based Localization algorithm for predict and minimize the average localization error.

// input 1: Nodes
// input 2: Network Simulation Area
// output: Average Localization error

⇒ Start
⇒ Choose FIS→ Tagaki Sugeno
⇒ Choose input1 →Nodes
⇒ Varying the Range of nodes → [15 30]
⇒ Choose the number of membership function for nodes → **3**
⇒ Choose the membership function nodes →Triangular
⇒ Choose the input2→ Network Simulation area
⇒ Varying the Range of Network Simulation area → [80 140]
⇒ Choose the number of membership function → 3
⇒ Choose the membership function → Triangular
⇒ Choose the output → Average Localization error
⇒ Choose number of membership function → 6
⇒ Choose the Output type → Constant
⇒ Specify the If-then rules
⇒ Choose the method for Defuzzification → wtever
⇒ Select Rule Viewer for assessment
⇒ Note Average Localization error for given inputs.
⇒ Select 3D-Surface Viewer
⇒ Stop

3.2 Defining Fuzzy Variables, Designing Membership Functions and rules for prediction and minimization of ALE

A fuzzy inference system, with inputs being the number of nodes, the network simulation area, and the output being the average localization error, modeled with the Takagi Sugeno method, is illustrated in Figure 2. The Simulation parameters are illustrated in Table 1.

Table 1. *Simulation scenario parameters*

Simulation Parameter	Value
Network simulation area in meter square	80 x 80 to 140 x 140
Number of anchor nodes	15 to 30
Radio range in meters	18
Average Localization Error in meters	1 to 4
Radio propagation model	Ideal, no path loss, no interference
Deployment model	Random

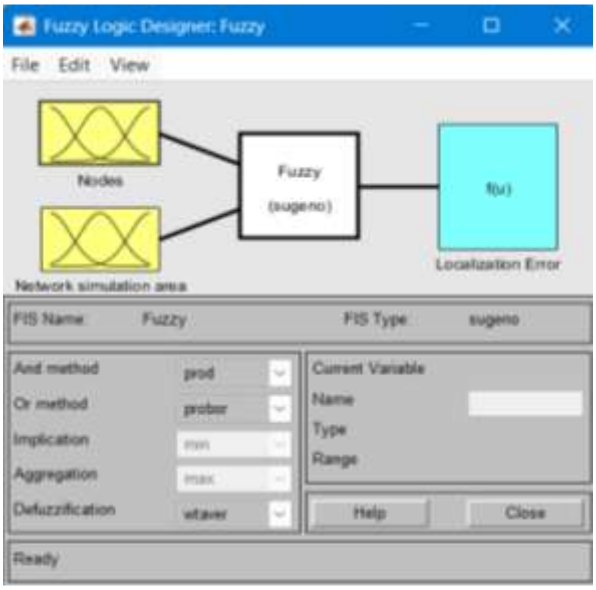

Figure 2. *Fuzzy inference system*

i. While the nodes can take a value between [15, 30], the space is divided into three triangular functions (low, medium, high) as shown in figure 3.
ii. While simulation area can take a value between [80, 140], the space is divided into three triangular functions (low, medium, high) as shown in figure 4.
iii. The output variable is a localization error and may take a value between [1, 4]. Divide the space into six parts: low, low, medium, medium low, medium, medium high, and high.
iv. Fuzzy rules are represented in an antecedent-consequence table to define the logical relationships within a fuzzy system. This table links antecedents (input conditions) to consequences (output actions) through if-then rules. The if-then rules are illustrated in Table 2.

By using a rule-based approach and membership functions, these systems can effectively handle uncertainty and imprecision, much like human reasoning. To refine performance and accuracy, the system's rule base and membership functions can be adjusted over time the system's output and performance are evaluated using the rule base and a

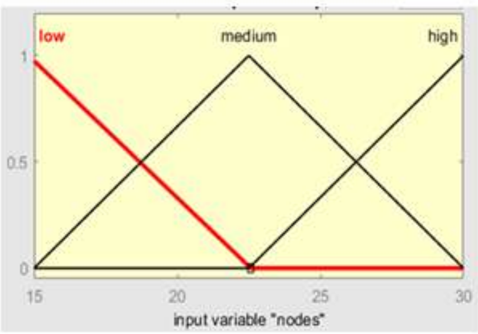

Figure 3. *Membership Functions for Nodes*

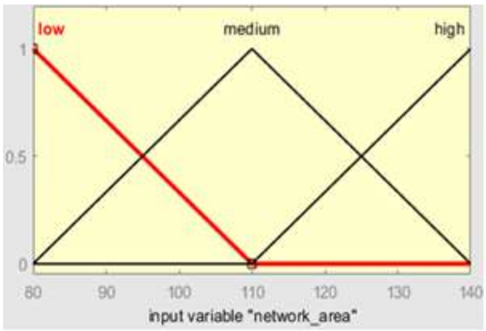

Figure 4. *Membership Functions for Network Simulation Area*

Table 2. *FUZZY rule base for tuning and predict the average localization error*

Rule	Antecedent	Consequent
Rule 1	IF : Nodes is low and network area is low THEN	Medium low
Rule 2	IF : Nodes is low and network area is medium THEN	Medium high
Rule 3	IF : Nodes is low and network area is high THEN	high
Rule 4	IF : Nodes is medium and network area is low THEN	Low medium
Rule 5	IF : Nodes is medium and network area is medium THEN	Medium
Rule 6	IF : Nodes is medium and network area is high THEN	Medium high
Rule 7	IF : Nodes is high and network area is low THEN	low
Rule 8	IF : Nodes is high and network area is medium THEN	Low medium
Rule 9	IF : Nodes is high and network area is high THEN	Medium low

surface viewer, providing a visual representation of the system's behavior. To further enhance accuracy, the output of the fuzzy system can be integrated with an Adaptive Neuro-Fuzzy Inference System (ANFIS). This hybrid approach combines the strengths of both techniques, leading to more precise and reliable results

4. ANFIS Based System to fine tune the parameters to predict and minimize the ALE

To further enhance accuracy and robustness, an adaptive neuro-fuzzy inference system (ANFIS) can be integrated. ANFIS combines neural network learning capabilities with fuzzy system interpretability. ANFIS can improve localization precision by automatically fine-tuning fuzzy rules and membership functions based on data. This interactive approach, which combines the benefits of fuzzy logic and neural networks, provides a powerful solution for precise and reliable localization in challenging environments.

4.1 Workflow of the ANFIS-based system.

The Takagi-Sugeno (TS) Fuzzy Inference System (FIS) is typically utilized to design the system. This sort of FIS can handle information faster than the Mamdani FIS, making it suited for complex scenarios. In this study, a TS FIS is created in MATLAB's ANFIS editor using triangle membership functions and hybrid learning to optimize both membership functions and fuzzy rule parameters, effectively estimating average localization error. The flow diagram of the ANFIS based system is depicted in Figure 5.

ANFIS training is a multi-stage approach. The process begins with data preparation and the creation of an initial fuzzy inference system (FIS). The FIS is then refined using hybrid learning approaches. Following training, the model's performance is evaluated against both training and testing data. Rule-based analysis is used to understand the extracted rules and learn about the model's decision-making process. Furthermore, surface-based analysis visualizes the input-output ANFIS training is a multi-stage approach. The process begins with data preparation and the creation of an initial fuzzy inference system (FIS). The FIS is then refined using hybrid learning approaches. Following training, the model's performance is evaluated against both training and testing data. Rule-based analysis is used to understand the extracted rules and learn about the model's decision-making process. Furthermore, surface-based analysis visualizes the input-output

4.2 The structure of the ANFIS-based system

An ANFIS-based system with five layers is aimed to forecast and minimize the average localization error. The input layer handles the system's inputs, specifically the number of nodes and the network

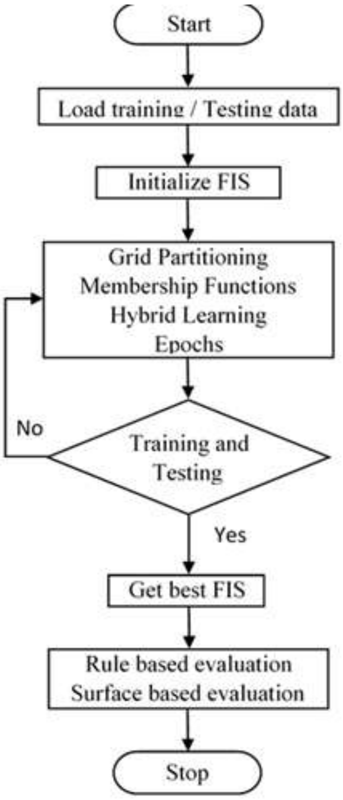

Figure 5. *The flow diagram of the ANFIS*

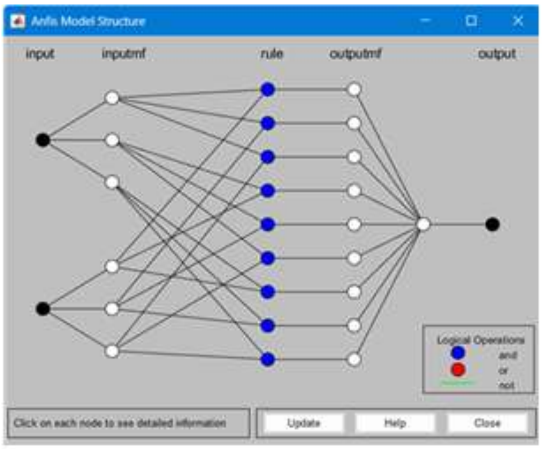

Figure 6 *The Structure of ANFIS based System*

simulation area. The fuzzification layer turns these inputs into fuzzy sets by applying relevant membership functions. The rule layer applies fuzzy rules to the inputs, calculating their firing strengths. The normalization layer changes the firing strengths to make them proportional. Finally, the output layer combines the normalized firing strengths to generate a crisp output that represents the expected average localization error. The structure of the ANFIS-based system is depicted in Figure 6.

4.3. Evaluation of ANFIS based system

Rule-based evaluation helps determine whether the fuzzy rules are consistent, accurate, and interpretable. Surface-based evaluation examines how effectively the system simulates the relationship between inputs (number of nodes and Network Simulation area) and the output(Average Localization error) across various scenarios.

These evaluations lead the tuning of the ANFIS system by refining the rule base and changing the surface fit, resulting in improved performance and minimized localization errors in a wireless sensor network. Figures 7 and 8 exhibit the surface viewer, and rule base respectively.

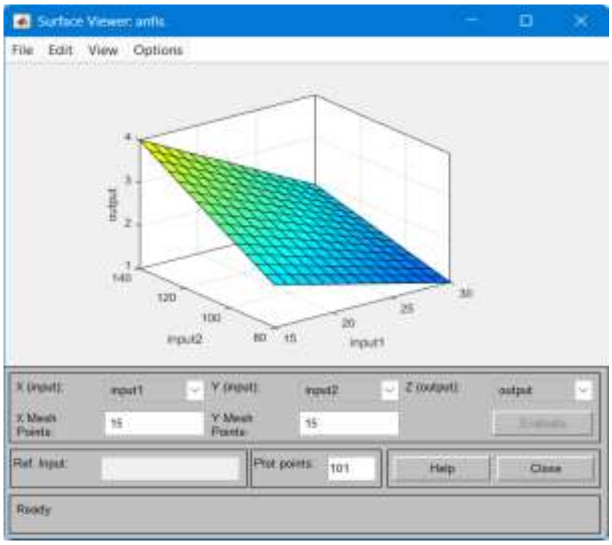

Figure 7*.The surface viewer of ANFIS based sysytem*

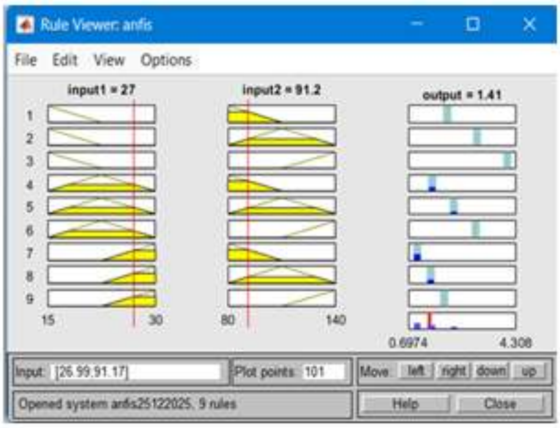

Figure 8 *The rule base of ANFIS based System*

5. Results and Discussions

5.1 Comparison of Simulated ALE and Predicted ALE

The performance of the FUZZY integrated with the ANFIS model was evaluated by comparing its predicted ALE values with simulated ALE from a modified range-free localization algorithm with a Kalman filter. The graph demonstrates that the ANFIS method provides the best performance in minimizing and predicting average localization errors. The modified range-free localization algorithm, Fuzzy, and ANFIS methods all have different levels of localization error, which can be seen in Figures 9 and 10.

Figures 9(a) and 9(b) provide a graphical representation of the average localization error. The network simulation areas are 100 x 100 m² and 120 x 120 m², respectively, with the number of nodes varying from 16 to 30.

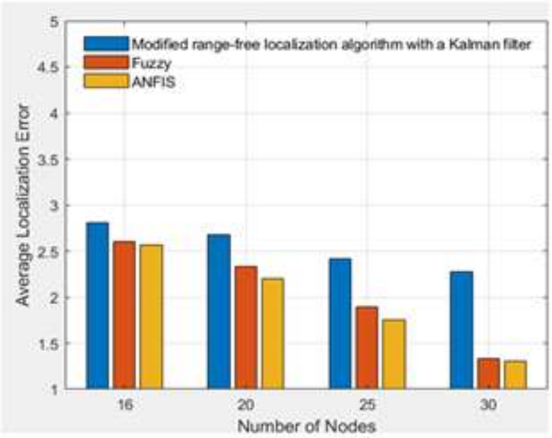

***Figure. 9(a)**. The number of nodes varies from 15 to 30, while the network simulation area is 100 x 100 m²*

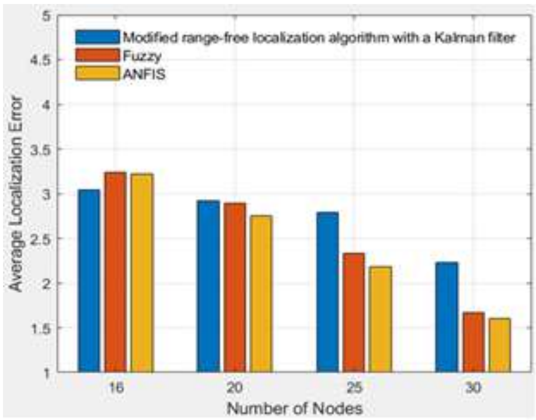

***Figure. 9(b).** The number of nodes varies from 15 to 30, while the network simulation area is 120 x 120 m²*

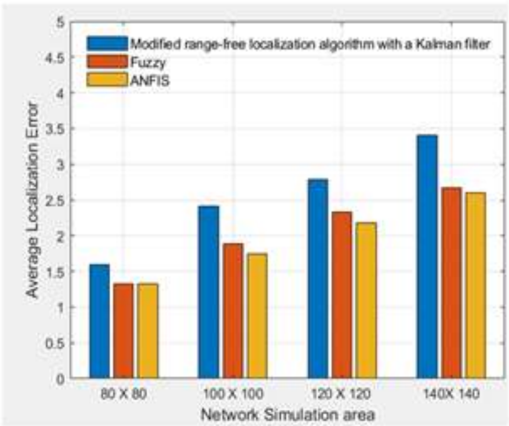

***Figure10 (a).** The network Simulation area varies from 80 x 80 m^2 to 140 x 140m^2 while number of nodes 25*

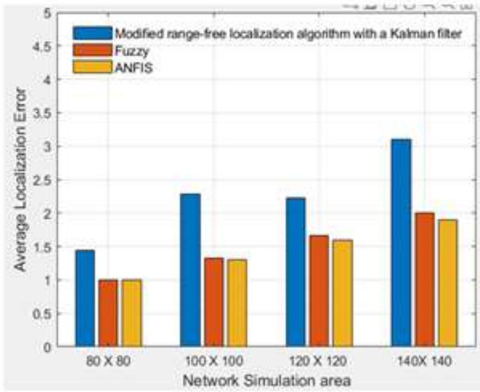

***Figure. 10(b).** The network Simulation area varies from 80 x 80 m^2 to 140 x 140m^2 while number of nodes 30*

Figures 10(a) and 10(b) provide a graphical representation of the average localization error. The number of nodes is 25 and 30, respectively, with the network simulation area varying from 80 x 80 m² to 140 x 140 m².

5.2. Correlation between Simulated ALE and Predicted ALE

The correlation between the FUZZY integrated with the ANFIS model and the modified range-free localization algorithm with a Kalman filter was determined using regression analysis and root mean square error (RMSE). The predicted ALE values of the FUZZY-ANFIS model were compared to the simulated results of the updated range-free localization technique. The predictions exhibited a high linear alignment with the simulated data, with negligible variation.

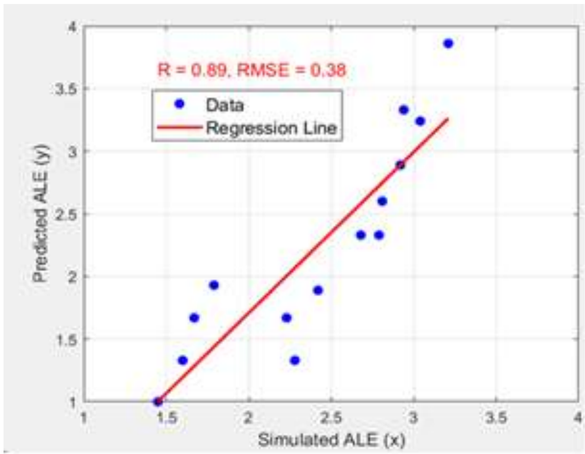

***Figure 11.** Correlation between Simulated ALE and Predicted ALE*

The correlation coefficient (R) = 0.89 and RMSE = 0.38, with a 95% confidence interval around the regression line, indicate a significant correlation between predicted and simulated values. Figure.11 is correlation between Simulated ALE and Predicted ALE.

6. Conclusions

In this work, a fuzzy integrated ANFIS-based model for prediction and fine-tuning of ALE was presented and investigated. A fuzzy-based system provides an effective approach for minimizing localization errors by dynamically tuning system parameters to adapt to varying environmental conditions. Fuzzy logic's capability to handle uncertainty and imprecision ensures flexibility and real-time optimization, making it well-suited for applications such as robotics, wireless sensor networks, and autonomous vehicles. Adding an adaptive neuro-fuzzy inference system (ANFIS) makes the system even more accurate and reliable by combining neural networks' learning abilities with fuzzy logic's ease of understanding. These methods are evaluated for their performance by using the correlation coefficient, it is a high correlation between predicted and simulated values. Fuzzy logic and ANFIS work well together to make a strong, flexible method for locating things reliably and accurately in tricky and complicated situations. Soft computing methods require significantly less time than traditional localization algorithms.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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